Quantifying Geoacoustic Uncertainty and Seabed Variability for Propagation Uncertainty

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LONG-TERM GOALS

Propagation and reverberation of acoustic fields in shallow waters depend strongly on the spatial variability of seabed geoacoustic parameters, and lack of knowledge of seabed variability is often a limiting factor in acoustic modeling applications. However, direct sampling (e.g., coring) of vertical and lateral variability is expensive and laborious, and matched-field and other long-range inversion methods fail to provide sufficient resolution. The long-term goal of this work is to use a Bayesian inversion approach in combination with seabed reflectivity data to investigate and quantify spatial variability of seabed sediments in two and three dimensions. For proper quantitative examination of spatial variability, it is important to differentiate between parameter estimate uncertainty, model parametrization effects, and actual spatial variability.

To date, the project has developed an approach to quantify spatial variability of seabed sediments along a track (Dettmer et al. 2009ab) of point measurements separated by several kilometers. More recently advanced and general *trans-dimensional* inversion techniques (Dettmer et al. 2010ab 2011a) have been developed which provide more realistic estimates of environmental parameter uncertainties than previously possible in the acoustics community. In addition, Dettmer et al. (2011b) developed a trans-dimensional sequential Monte Carlo (SMC) algorithm to carry out seabed parameter inference on large data volumes along range-dependent tracks, providing two-dimensional (2D) geoacoustic uncertainty models of high vertical and lateral resolution. Further development of this methodology is an ongoing effort that will lead to rigorous 2D and three-dimensional (3D) geoacoustic uncertainty estimation from towed-array data in complex shallow-water environments (Holland et al. 2011).

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OBJECTIVES

The objective of this research is to develop new methodologies to estimate 2D geoacoustic parameters and quantify uncertainties to permit prediction of sonar performance uncertainties, as a step towards full 3D uncertainty estimation and verification. Highly informative seismo-acoustic reflectivity data collected along range-dependent tracks are used to carry out geoacoustic inference. Such data can be collected using ship-towed or autonomous vehicle-towed arrays (Holland et al. 2011) and geoacoustic uncertainties can be inferred using trans-dimensional SMC algorithms. One-dimensional inversion results of wide-angle reflection data are used as benchmarks at points along the track. Other available data can be used when available (e.g., high-resolution seismic, other towed-array acoustic data, AUV data, information from geologic interpretations) to improve results. The methodology is being developed using a variety of existing data.

APPROACH

To predict sonar performance uncertainties, 2D geoacoustic uncertainty models are needed along the track of interest. This project originally intended to develop such uncertainty models for the QPE experiment, where a $\sim$50 km x 50 km area off northeast Taiwan was chosen, including part of the Chilung shelf, the East China Sea shelf and upper slope. Unfortunately, weather and safety concerns prevented data acquisition. Thereafter, the focus shifted to spatially densely sampled wide-angle reflection data from the Malta Plateau in the Mediterranean Sea (Holland et al. 2011). These data provide a basis for developing and demonstrating the ability to recover rigorous high-resolution 2D geoacoustic uncertainty models.

Inferring geoacoustic parameters requires the assumption of a model describing the observed physical system including the physical theory, its appropriate parametrization, and a statistical representation for the data-error processes. In the past, Bayesian inference has been applied widely to geoacoustic inverse problems; however, model selection and comparison has seen only limited applications in acoustics. In addition, ambiguity and subjectiveness in the choice of model causes parameter uncertainties that have been ignored in geoacoustic inversion. The choice of model parametrization strongly influences parameter uncertainty estimates, with under-parametrized models generally under-estimating uncertainties while over-parametrized models over-fit the data and over-estimate uncertainties (Dettmer et al. 2009a; Dosso and Dettmer 2011). Additionally, since the model is an approximation of the actual environment, the ambiguities resulting from this approximation cause parameter uncertainties that should be accounted for by integrating over the range of applicable parametrizations. In addition, parameter estimates can appear biased if an inappropriate parametrization is chosen.

One approach to address these issues is to compute the Bayesian evidence, which measures the likelihood that the observed data occurred given the model under consideration. Bayesian evidence is a powerful but computationally difficult concept and was used by Dettmer et al. (2010b) in geoacoustic inversion to pick the most likely model parametrization. Bayesian evidence is particularly useful when an investigator is interested in how different choices of physical theory are supported by a measured data set, but can be computationally expensive when many possible environmental parametrizations (e.g., the number of sediment layers) need to be considered. To address the latter, a trans-dimensional formulation of the geoacoustic inverse problem has been developed, where the number of parameters (environmental, data-error model, etc.) is itself an unknown in the problem (Dettmer et al. 2010a). This results in a trans-dimensional posterior probability density (PPD) that intrinsically addresses model

selection and accounts for parameter uncertainty due to the range of model parametrizations by integrating over possible parametrizations rather than picking a single model. Trans-dimensional inference was introduced by Green (1995) and has since been applied to several problems in geophysics.

To sample from trans-dimensional distributions, Green (1995) generalized the Metropolis-Hastings (MH) algorithm to the reversible-jump Markov chain Monte Carlo (rjMCMC) sampler that allows the Markov chain to transition between dimensions of the state space (i.e., the model parameter space) while maintaining detailed balance of the chain to obtain unbiased estimates. The rjMCMC formulation is based on an extended acceptance rule similar to MH acceptance and can be applied to a wide range of problems and dimension transitions. The rjMCMC methodology in this work also applies a partition modeling approach and trans-dimensional jumps of the birth-death form that allow for a straightforward implementation and application to AUV data. The partition model is applied to the layering structure of the seabed sediment by describing the sediment as an interval over a certain depth with layer interface locations determined by the data. The partition model together with a trans-dimensional approach results in a naturally parsimonious self-regularization that is driven by the data (Bodin and Sambridge 2009; Dettmer et al. 2010a). Results combine the ability to resolve sharp discontinuities as well as to approximate smooth transitions (such as gradients) of arbitrary shape as determined by the data. The integrated "map" of interfaces shows increased probability where the data support structure.

A significant challenge in trans-dimensional inversion is addressing data errors when serial data-error correlations are present. Such error correlations can be described by a covariance matrix in the likelihood function (Dettmer et al. 2009b; Dosso and Dettmer 2011). Point estimates of this matrix can be obtained by computing predicted data for a best-fit model and taking the difference of the observed data and the prediction as a sample of the true data errors. However, such estimates can be problematic in trans-dimensional inversion, as they are representative of a fixed-dimension only. Dettmer et al. (2011a) propose a parametric approach to data-error correlation modeling for trans-dimensional problems using autoregressive error modeling to address these issues.

To apply trans-dimensional inversion to large data volumes along tracks in range-dependent environments, Dettmer et al. (2011b) developed a sequential method which is able to quantify geoacoustic uncertainty along a track in an efficient manner. The SMC (particle filter) algorithm uses rjMCMC steps, allowing the particles to find the seabed parametrizations consistent with information provided by data and prior knowledge. The algorithm can be applied to sequences of reflection-coefficient data acquired along tracks using towed or other arrays.

WORK COMPLETED

In the third year of this project, work has focused on extending new approaches to quantifying environmental parameter uncertainty for geoacoustic inversion (Dettmer et al. 2011ba). These new techniques have been applied to initially analyze data that were collected by Charles Holland and Peter Nielsen on the Malta Plateau by using an AUV with a Chirp source and a 32 element towed array. The 170 core high performance compute cluster has been extensively used to support this research. The cluster is jointly funded by ONR and the Natural Sciences and Engineering Research Council (NSERC) of Canada. Several of the inversion algorithms for this project have been developed to take full advantage of the massively parallel architecture of the cluster.

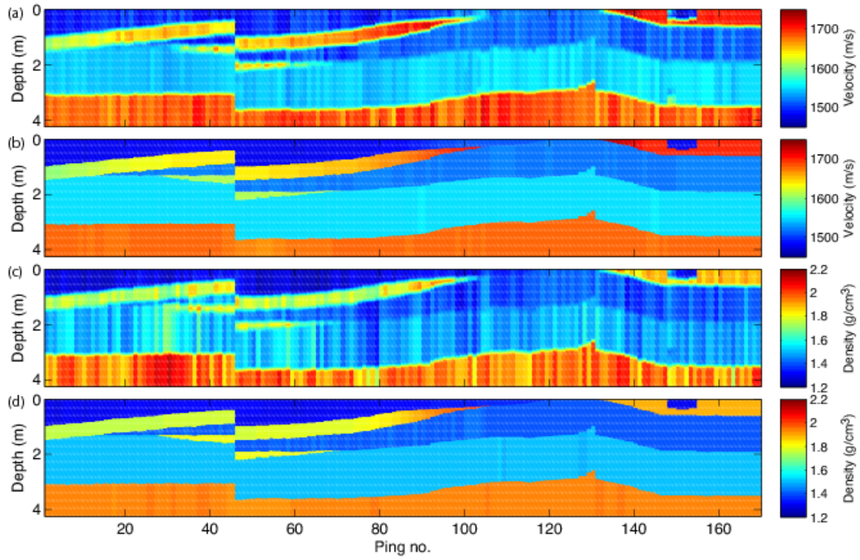

Figure 1: True simulated environment [(b) and (d)] and posterior-mean model sequential inversion results [(a) and (c)] for sound velocity and density (attenuation not shown).

RESULTS

Results presented in this section focus on some of the research carried out this year to develop a new approach to quantify geoacoustic uncertainty along range-dependent tracks. A more complete account is presented in Dettmer et al. (2011a), Dettmer et al. (2011b), and Holland et al. (2011).

Figure 1 shows a simulated environment for a track sampled by 170 consecutive data sets (Fig. 2). Each data set represents a spatially confined, independent part of the seabed, separated by $\sim$10 m. The true environment (Fid. 1) includes both smooth variations in geoacoustic properties along the track as well as several large and abrupt changes (including a geological fault and an erosional channel). The overall number of layers (not counting the basement) starts with 3 layers at ping 1, increases to 6 at the fault, decreases to 2 at ping 124, and again increases to 3. The data for the four pings in Fig. 2 highlight the significant changes caused by the fault and erosional channel. The fit of the particle cloud as represented by predictions for 200 randomly drawn particles and 95% highest probability density credibility intervals is also shown.

Figure 3 shows the probability of interfaces as a function of depth along the track. This form of marginalization recovers layering structure in a manner similar to sub-bottom profilers. However, unlike standard sub-bottom profilers, Fig. 3 represents a quantitative map of true interface-depth probabilities that does not require an arbitrary scaling velocity to convert two-way time to sub-bottom depth. In addition, the interface-depth probability also indicates the sharpness of the discontinuity (i.e., the size of the impedance contrast and the depth interval over which the data are sensitive to it). The results show that interfaces are successfully identified by the partition model and are tracked from ping to ping where supported by the data. In addition, layers are successfully detected or deleted when they appear or disappear, respectively.

The inversions carried out along the range-dependent track result in posterior distributions allowing for

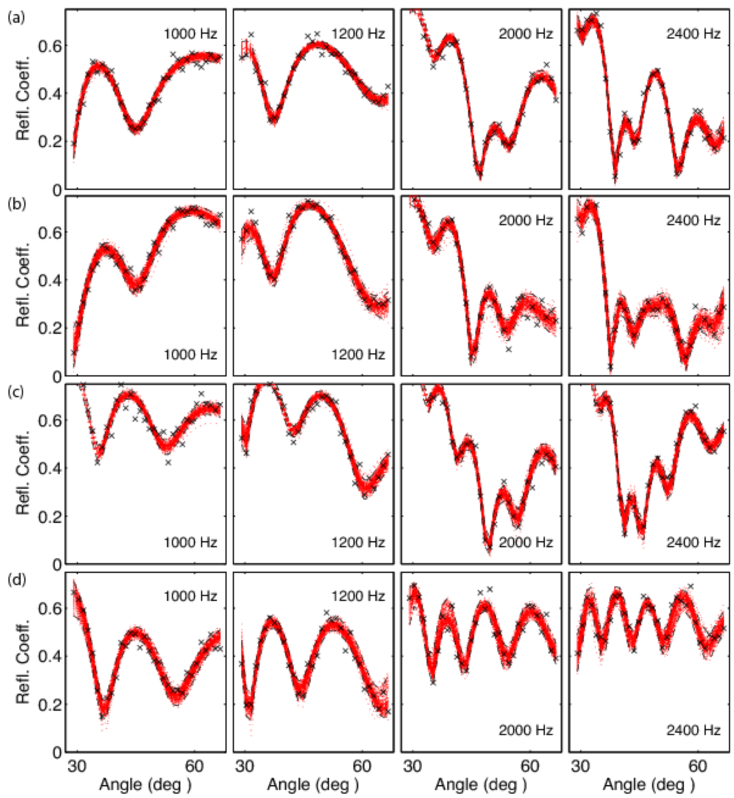

Figure 2: Simulated reflection-coefficient data (crosses) and ensemble fit (dotted lines) for pings before and after the fault event [pings (a) 45 and (b) 46], and before and within the erosional channel [pings (c) 146 and (d) 152]. Also shown are the 95% HPD credibility intervals for the predicted data for the entire particle cloud (dashed).

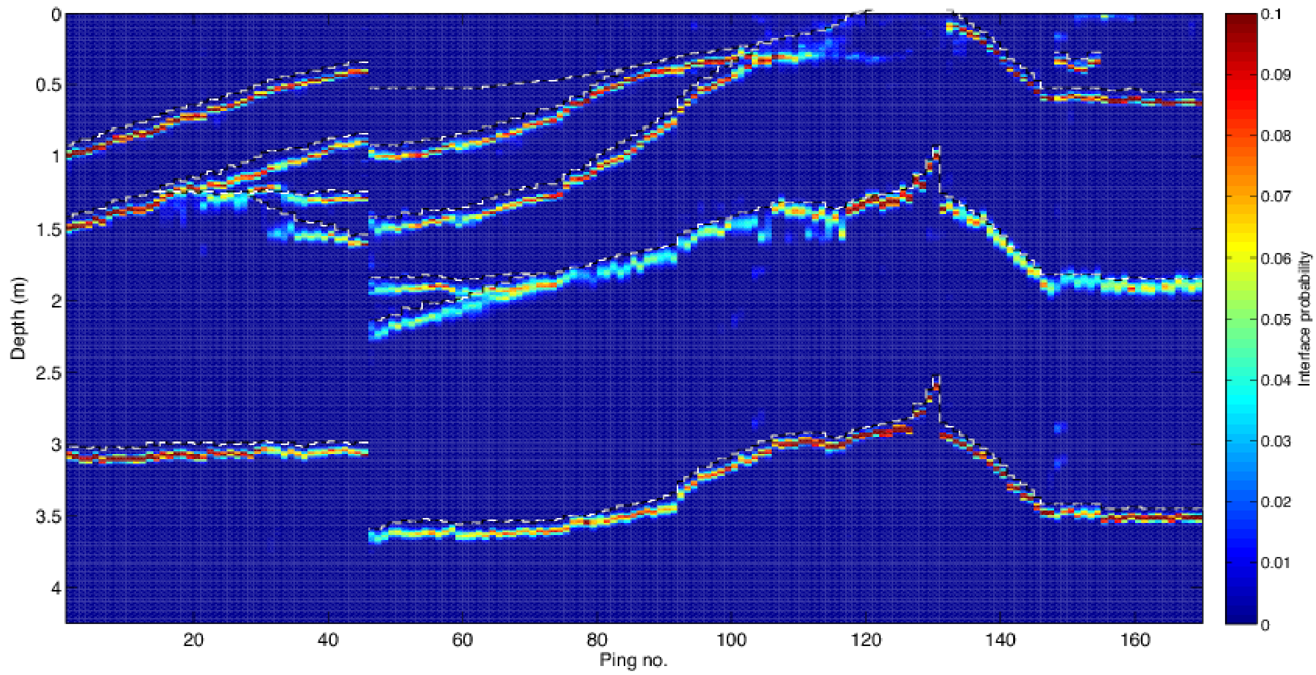

Figure 3: Interface-depth probability distributions along the track. True interface locations are shown as dashed lines which are offset slightly for display purposes.

detailed inference of various parameter properties, including parameter uncertainties and inter-relationships. Figure 1 shows the posterior-mean model results for the sequential algorithm, indicating that the true environment is successfully inferred from the simulated data. Figure 4 shows a detailed analysis of the parameter uncertainty (a) just before and (b) just after crossing the geologic fault. Geoacoustic parameter uncertainties are shown in terms of marginal profile distributions that illustrate the uncertainty of geoacoustic parameters as a function of depth. Profile marginals are considered for velocity, density, and attenuation. The true environment is given as a dashed line in the profile marginals. Further, the location of the results for the pings is marked as a dashed line along the track to emphasize that such posterior analysis can be displayed for any ping of interest. In addition, interface probability marginals are plotted as a function of depth, quantifying the probability of interface locations. Interface probability marginals such as these are the basis for interface probability maps (Fig. 3). Marginal distributions of the number of interfaces in the partition show the support of the data for the different model parametrizations. The number of interfaces detected by the trans-dimensional SMC algorithm does not change when the fault is crossed since the velocity and density contrasts are very small between the top-most sediment before the fault and the top-most sediment after the fault. The interface probability in Fig. 4 shows a wider spread and the profile marginals show some complicated (multi-modal) structure that is likely due to the difficulty the fault poses for algorithm convergence. However, the results quickly stabilize over the next few pings following the fault.

Figure 5 shows inversion results of applying the SMC algorithm to data collected by Charles Holland and Peter Nielsen using an AUV towed array with 32 hydrophones. The experiment was carried out on the Malta Plateau, Mediterranean Sea. Due to the experiment geometry (AUV 12 m above the seafloor, source and array towed 10 m behind the AUV, 1 m hydrophone spacing), the reflection coefficient data

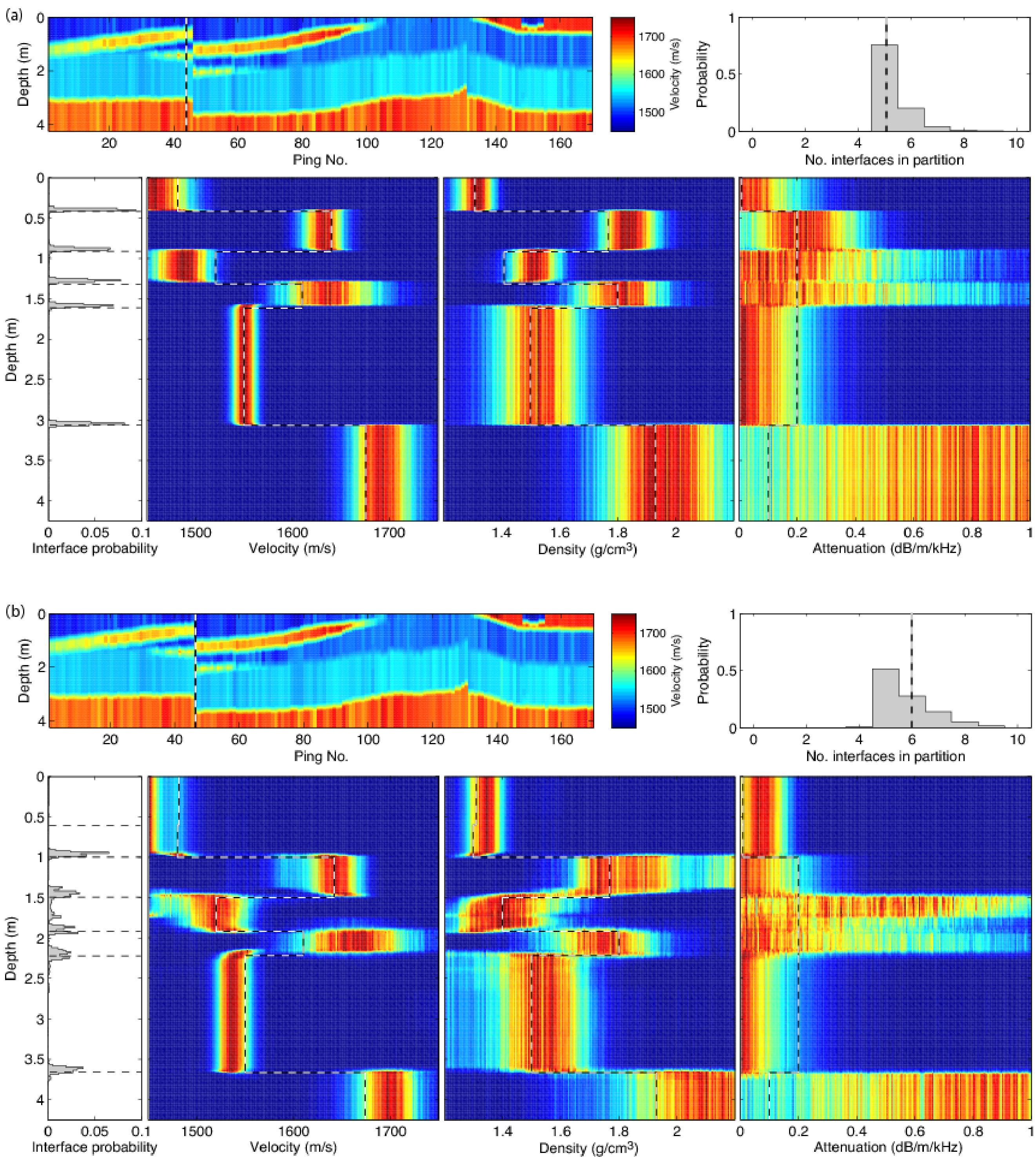

***Figure 4:* Profile marginal distributions for (a) ping 44 before the fault and (b) ping 46 immediately after the fault. True parameter values are given as dashed lines and the location of the pings is indicated as a dashed line along the track.**

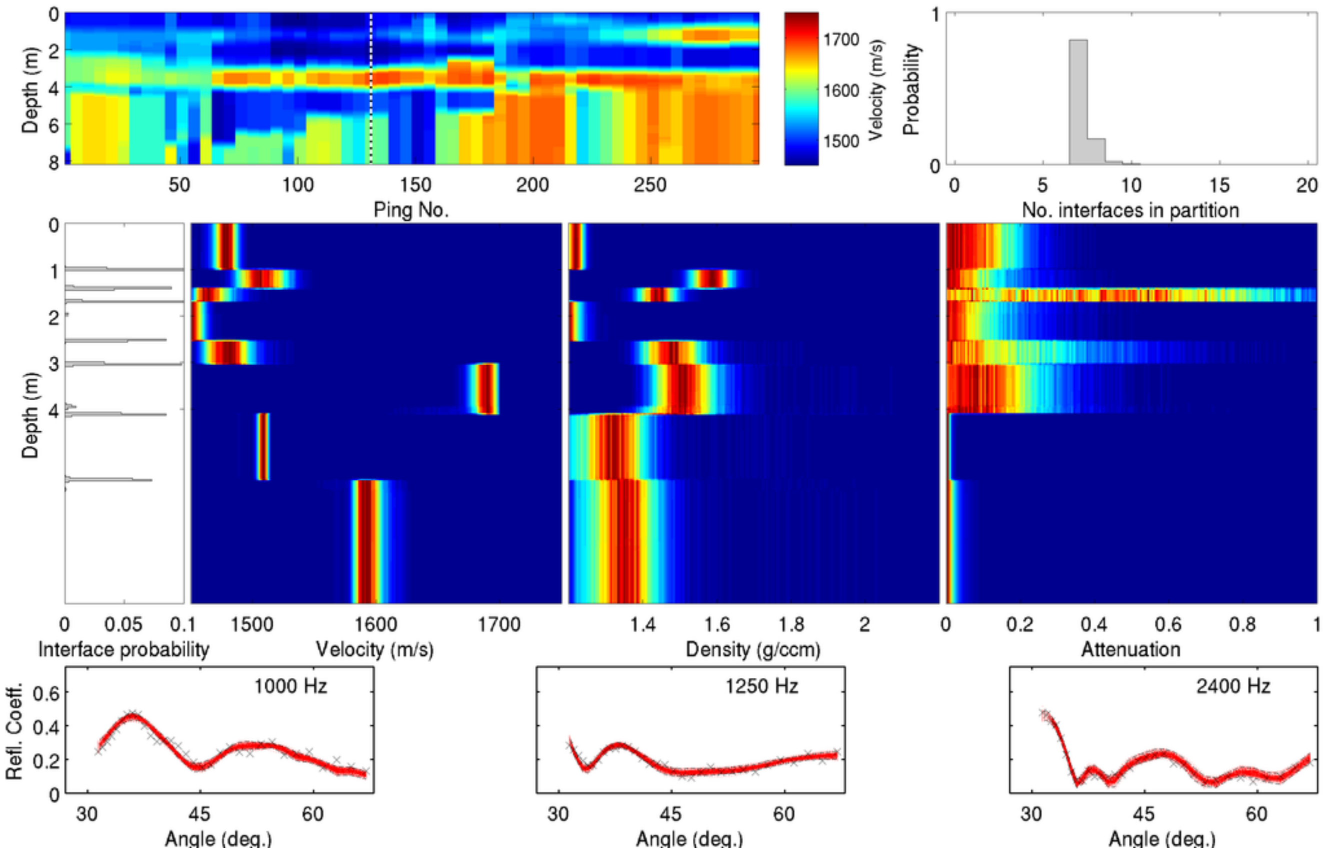

Figure 5: ***Profile marginal distributions for ping 131 of the AUV measured data. The mean velocity model along the track is given in the top-left panel with the location of ping 131 indicated as a dashed line. The top-right panel shows the interface marginal distribution, and the center panels the interface-, velocity-, density-, and attenuation-depth marginal profile distributions.***

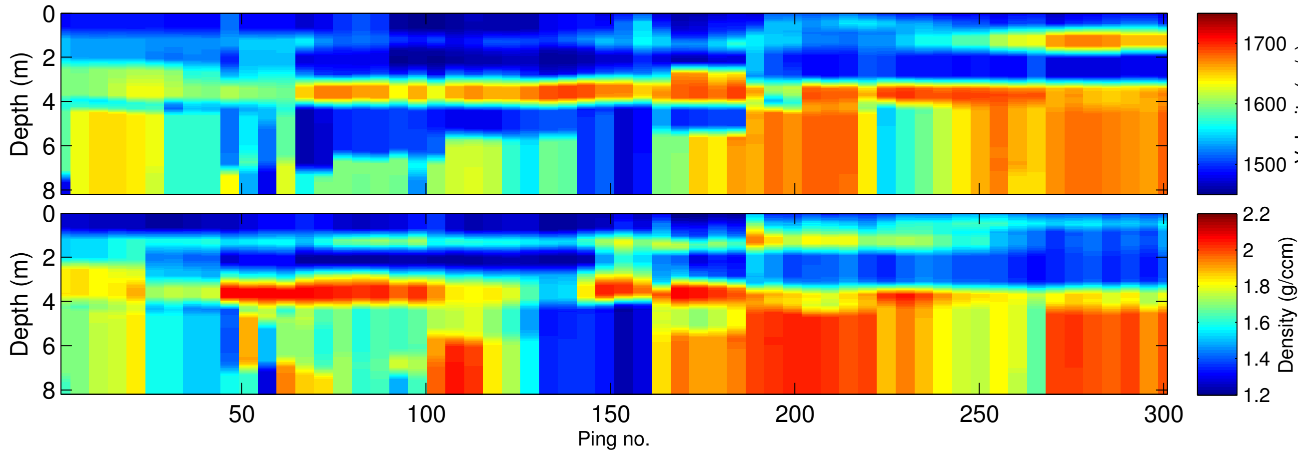

Figure 6: Inversion results for AUV-measured data in terms of posterior mean models for (a) velocity and (b) density along the fist 300 pings of the track.

shown in the bottom row of Fig. 5 are the spherical reflection coefficient. To carry out the inversion, Holland and Dettmer developed an efficient reflection-coefficient forward model that accounts for spherical-wave effects (by means of plane-wave decomposition Holland et al. (2011)). The model is efficient enough to be used in a trans-dimensional inversion (a significant challenge), given the UVic parallel computing facility.

The algorithm was applied to every 5th ping for 60 pings, providing results covering the first ∼300 pings of the AUV track. Figure 6 shows the mean velocity and density structure along the first ∼1.5 km (300 pings) of track. It can be seen that some consistent structure exists along the track, in particular, a high-velocity layer between 2- and 4-m depth. Other weaker layers are also present in shallow parts of the seabed. The basement structure is much less resolved which is common for reflection-coefficient data.

IMPACT/APPLICATIONS

The ability to obtain seabed parameters remotely (i.e., without direct sampling) has important implications for science (e.g., providing data for understanding sediment processes), the Navy (improving databases for ASW and MCM), as well as many commercial applications (pipeline or cable laying). A particular strength of the present work is quantifying the uncertainties of the seabed parameters for large data volumes and in a rigorous manner that has not to date been available in geoacoustic inversion. Two-dimensional geoacoustic uncertainty models will impact the reliability and quality of transmission loss prediction.

RELATED PROJECTS

- Broadband Clutter JRP project (NURC, ARL-PSU, DRDC-A, NRL)
- ONR QPE Uncertainty Program
- Dossos NSERC Discovery Grant "Geoacoustic Inversion" (2009-2014) at the University of

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- “Bayesian ambient noise inversion for geoacoustic uncertainty estimation” (2011–2012, Jorge Quijano ONR Postdoctoral Fellowship N000141110214) (Quijano et al. 2011).
- “Bayesian inverison of seabed scattering data” (2011–2013, Gavin Steininger ONR PhD Fellowship N00014110213).

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